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Computational Modeling of Crude Oil Price Forecasting: A Review of Two Decades of Research

Lubna A Gabralla[1], Ajith Abraham[1, 2]

[1] Faculty of Computer Science & Information Technology,
Sudan University of Science Technology, Khartoum, Sudan
lubnagabralla@gmail.com

[2] Machine Intelligence Research Labs (MIR Labs)
Scientific Network for Innovation and Research Excellence, WA, USA
ajith.abraham@ieee.org

***Abstract*: Oil embodies a vital role in the world economy as the backbone and origin of numerous industries. It is an important source of energy representing an indispensable raw material and as a major component in many manufacturing processes and transportation. Oil price suffer from high volatility and fluctuations. In global markets, it is the most active and heavily traded commodity. Recently many studies emerged to discuss the problem of predicting oil prices and seeking to access to the best outcomes. Despite these attempts there were no enough studies that could be used as a reference covering all aspects of the problem. In this research, a comprehensive survey covering the previous methods and some results and experiments are presented with a focus on and maintaining the necessary steps when predicting oil prices.**

Keywords: oil prices, volatility, forecasting , prediction models

I. Introduction

The industrial revolution began by using traditional sources with coal combustion and hydropower. As main sources of electricity, and then later began to use oil and nuclear energy as a major participant of energy [1]. Oil is a wealth non-renewable and it is distributed randomly all over in the ground [2]. Tuo et al. [2] indicated that the study of oil prices according to Harold Hotelling the well-known mathematical economist in 1931who talked about market analysis by using tools of economics, exhaustible resources and developed the basic theoretical structure to the economics of energy research. Oil embodies a vital role in the national and international economies as the backbone and the source of raw inputs for numerous industries. It is an important source of energy and represents indispensable raw material as a major component in many manufacturing processes and transportion fuel. According to the Energy Information Administration (EIA), the world currently consumes 85.64 million barrels of crude oil daily [3]. It represents the largest proportion of the world's energy consumption compared to other sources [4]. Oil price is suffering from high volatility and Fluctuations. In global markets it is the most active and heavily traded commodity. This volatility is up to approximately 25% per annum [5]. This rate that cannot be ignored for its influence in the world economy, particularly in developing countries. Sharp oil price movements, dramatic uncertainty for the global economy and trends in changing oil prices has an impact on world politics, economy, military and all sectors of society. So increasingly important is the interests of government, companies and investors on this issue. Figure 1 shows oil prices and their volatility. Desiging a model to predict the prices of crude oil with accuracy and high performance as one of the most valuable academic topics researched to solve the problem of fluctuating oil prices. Therefore our survey aims to provide a broad overview for predicting oil prices methods in order to assist researchers to access optimal model to solve this problem.

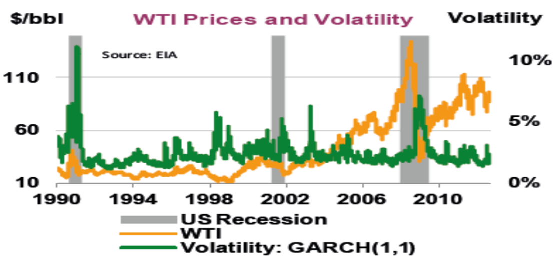

Figure 1. Oil prices and volatility [91]

This survey is an attempt to describe the approaches that were used in predicting oil prices taking into account of the general steps used in prediction in addition to the investigation of the relation between economic variables and oil while highlighting the most important factors that has impact in the volatile oil prices. The article is organized as follows. In Section 2, we provide briefly the related works clustered as three groups: the correlation between Oil Price and Economic Variables; the characteristics of the main factors and oil price volatility and forecasting models . In Section 3, we describe the various datasets that were used previously and then present different data pre-processing techniques and performance evaluation. Finally, Section 4 provides concluding remarks.

II. Related Literature

We mentioned about the importance of oil and their effects on the local and global economy. Therefore it has attracted the attention of researchers and authors to study it from different aspects and different categories. In the academic literature, prediction of oil prices were discussed in different formats. For example Xie et al. [6] divided the literature as:

a) Oil prices are confined between demand and supply framework.

b) Oil price volatility analysis

c) Oil price forecasting.

Tuo and Yanbing [2] designed three parts for oil price forecasting models. In the formal model, those factors affecting the analysis of oil prices, theoretical model were more disbursed to notice the behavior of market structure and simulation models as represented by information technology. Azadeh et al. [7] categorized forecasting methods according to the time schedule long-term, short-term and medium term. Also authors mentioned other classifications based on qualitative methods, regression methods, multiple equation methods and time series methods. Pan et al. [8] analyzed as three parts:

a) Future as predictor of oil price

b) Economic models to explain the prediction

c) Intelligent computing models to predict oil price

Weiqi et al. [9] , Wang et al. [10] , Xie et al. [6] classified forecasting methods as qualitative and quantitative. Zhang et al. [11] grouped the studies for analysis and predicting of crude oil price structure into two categories: models and data-driven methods. Our survey concentrates on three main parts:

a) Correlation between oil price and economic variables

b) The characteristics of the main factors

c) Oil price volatility and forecasting models.

A. Correlation Between Oil Price and Economic Variables

Generally the oil resource in the world is limited, so the needs for oil continue to the rise and production continues to fall in 1999, the price of crude oil ranged about $16 a barrel . By the year 2008, it had passed the $100 a barrel and fluctuated between $147.96 and $69. Achieving unprecedented shock and wide fluctuations that have significant impact and negative effects on petroleum exporting countries and consuming oil countries [8]. We must deal with the relationships between oil and economic factors correctly in developing our country and build a healthy economy and avoid the risk of sudden oil fluctuation and their impacts . Therefore, several studies focused on the correlation between oil future price and some other economic variables.

1) Oil price fluctuations and U.S. dollar exchange rates

It is considered that the price of oil and exchange rates of other currencies against the U.S. Dollar price of the most important commodity in global economic markets .various researches tried to understand the relationship between the price of oil and the US dollar real exchange rate. Lizardo et al. [12] concluded that an inverse relationship between oil prices and the value of U.S. Dollar in the long-term more lead to an increase in oil prices to a decrease U.S. Dollar rate for the oil exporting countries, while the importers of oil currencies goes down compared to the USD value. Akram [13] proved that there is the strength of non-linear negative correlation between the value of the Norwegian krone and the crude oil price used to the 4608 daily observations during January 1, 1986 , August 12, 1998 for the ECU index and the Brent. While Bénassy [14] provided evidence that a 10% rise in the oil price leads to a 4.3% appreciation of the dollar in the long term but they couldn't explain the increase in the oil with the decline in the U.S. Dollar exchange rate in the period from 2002 to 2004.

2) *The role of financial speculation in oil price*

Morana [15] investigated that financial shocks have played an important role in determining the oil price by increasing its 44% out of the 65% real oil price during the period of 2004-2010.

3) Relationship between oil prices, interest rate, and unemployment

Doğrul and Soytas [16] provided the evidence that oil prices and interest rate have clear impact on the unemployment in the long run case in the markets of Turkey. Their study covered the period from January 2005 to August 2009 .

4) Crude oil and stock market

Park [17] applied multivariate VAR analysis of the real stock returns of the U.S. and 13 European countries in the period January 1986 to December 2005 their results shows that oil price shocks have 6% a statistically significant impact on real stock returns. Jammazi [18] applied wavelet analysis and Markov Switching Vector Autoregressive (MS-VAR) method in the stock market returns for France , Japan and UK, in the period from January 1989 to December 2007 to identify the impact of the crude oil (CO) shocks on the stock market returns. Similarly Li et al. [79] achieved the strength of the relationship between the stock market in china and oil prices which are visible in the short term, investors adjusted their portfolios in accordance with the rise or fall in oil prices in order to avoid the risks. The data used cover the period from 1996:1 to 2009:12.

5) *Precious metal prices*

Jain et al. [19] concluded that higher oil prices lead to increased rates of inflation in oil-importing countries and therefore gave gold investors a hedge against this inflation, depending on the price of gold and precious metals (platinum and silver). Table 1 illustrates more examples for correlation between Oil Price and economic variables in previous studies.

B. The Characteristics of the Main Factors

Crude oil prices movements are even chaotic and very complex nonlinear time series which is frequently influenced not only by control the economic rules but also by numerous factors and many other complicated factors such as supply , financial shocks, GDP growth, crude oil distillation capacity, dollar index, weather conditions, heating oil price, OPEC oil policy, stock market, oil consumption of non-OECD, political stability and events, consumer expectations,gold ,financial speculations, inventories, economic prospects, exchange rates, and surplus capacity, demand and so on [4-7], [20-23], [24-25]. For the purpose of understanding the factors that affect the volatility of oil prices, many scholars studied these factors in an attempt to understand the role and their impact analysis in oil prices for example Hamilton, James [26] analyzed the factors that play roles in the fluctuation of oil prices, such as OPEC and control inventory supply and the impact of commodity speculation**.** Jinliang [20] analyzed the relationship between oil and gold to assess for more precision one prediction of oil prices used by the organizers of the study wavelet-based Boltzmann cooperative neural network and kernel density estimation (WBNNK) model, the results showed that the model has higher prediction accuracy. Wang et al. [27] attributed the volatility of oil prices to three main factors:

a. Increase in demand and supply shortages possibly caused by economic growth or the behaviors of oil producing countries
b. Exogenous events such as wars, natural disasters, etc.
c. Endogenous factors such as speculations in the markets.

Zhang et al.[28] proposed an EMD- model for the analysis of events to see its impact on oil prices , and to explain the method of how to work for authors who presented the first Gulf War 1991 and the Iraq War 2003 as an example. In this paper, as reported in the literature, we illustrate some factors that contributed to the decline or rise in oil prices. More details are as follows

1) Gold

Economists explain the increase in the gold price with the rise in oil prices as the results of investors hedge against inflation caused by the oil price shock , so gold is used to predict oil prices Similarly, the oil is used in models to predict gold prices [29][103].

***Table 1*:** Correlativity between Oil Price and Economic Variables

Ref	Economic variable	Target Country for the study	Aim of the study	Results and conclusion
[73]	Stock markets	UK, France and Japan	Examine the relationship between crude oil shocks and stock markets.	Rises in oil prices has an important role in determining the extent of stock returns change.
[74]	Stock markets	Germany, U.S Belgium, Spain, Greece, Sweden, U.K., Finland, Italy, Denmark, Austria, France, and Netherlands	The Impact of Oil Price Shocks on Stock returns Market in the in the U.S. and 13 European Countries	Oil price shocks account for a statistically significant 6% of the volatility in real stock returns
[75]	Stock markets	China	Relationships between oil price shocks and Chinese stock market	The oil price shocks not appear major impact on stock returns in most of the Chinese stock markets, except for some stocks of oil companies and manufacturing industries.
[76]	Exchange rate , prices of metal, interest rate	Turkey	The relationship between oil prices, the exchange rate of the local currency Turkish and the U.S. dollar , the prices of metals such as gold , silver and Turkish interest rate	The precious metals in Turkey and the exchange rate does not help to improve the forecast of the global oil and authors find the initial effects of oil prices on the precious metals markets
[77]	Exchange rate	India	Investigate impact of crude oil shocks on exchange rate link for India	An increase in the oil price return leads to the low price of Indian currency comparison US dollar and oil price shocks have the continuous effect of exchange rate volatility
[80]	Gold & euro	USA	Examines the interrelationships between the price of gold, oil and the euro	The relationship between gold and the euro either weak. Euro and oil all of them affects of the other in the same power to influence, the outcome of the proposed model that significantly affects oil in gold and the euro more than their impact on oil.

2) The supply of the international oil

Organization of Petroleum Exporting Countries (OPEC) and non-OPEC members are suppliers of oil at the global level , these countries especially the members of OPEC oil reserves are keen to maintain it to remain at an appropriate level of safety against risks therefore increasing demand for this stock leads to an increase in oil prices [27].

3) Demand of the international oil

The continuous increase in oil demand are the fundamentals behind the volatility of oil prices . This increase of oil demand produces economic growth and we all know that oil wealthy are depleted and their widening gap over the time between the increase in demand and production, this indicate that a rise in oil prices in the future will be a realistic issue [27]. Table 2 presents global oil demand (2011-2017).

***Table* 2:** Global oil demand (2011-2017) [91]

(million barrels per day)

	1Q11	2Q11	3Q11	4Q11	2011	1Q12	2Q12	3Q12	4Q12	2012	2013	2014	2015	2016	2017
Africa	3.4	3.3	3.2	3.4	3.3	3.4	3.4	3.4	3.4	3.4	3.5	3.6	3.8	3.9	4.0
Americas	30.3	30.1	30.7	30.4	30.4	29.7	30.2	30.7	30.6	30.3	30.5	30.6	30.7	30.8	30.9
Asia/Pacific	29.0	27.7	27.8	29.2	28.4	30.0	28.6	28.4	29.7	29.2	29.5	30.1	30.9	31.6	32.3
Europe	15.0	14.9	15.5	14.9	15.1	14.5	14.6	15.1	14.7	14.7	14.5	14.5	14.4	14.4	14.3
FSU	4.2	4.4	4.6	4.6	4.4	4.4	4.5	4.7	4.7	4.6	4.8	4.9	5.1	5.2	5.2
Middle East	7.0	7.4	7.8	7.3	7.4	7.2	7.7	8.0	7.5	7.6	7.8	8.1	8.4	8.7	9.0
World	**88.8**	**87.7**	**89.5**	**89.8**	**89.0**	**89.2**	**89.0**	**90.4**	**90.6**	**89.8**	**90.6**	**91.8**	**93.2**	**94.5**	**95.7**
Annual Chg (%)	2.5	0.5	0.8	0.3	1.0	0.5	1.4	0.9	0.9	0.9	0.9	1.4	1.5	1.4	1.3
Annual Chg (mb/d)	2.1	0.4	0.7	0.3	0.9	0.5	1.2	0.8	0.8	0.8	0.8	1.2	1.3	1.3	1.2
Changes from last MTOGM (mb/d)	-0.17	-0.10	0.13	-0.07	-0.05	-0.73	-0.27	-0.39	-0.54	-0.48	-0.93	-0.88	-0.68	-0.54	

4) *Political factors*

We mentioned earlier that the security and political situation in the oil - rich Middle East such as the first and second Gulf War , the search for weapons of mass destruction in Iraq and their consequence , Iran nuclear threats and political tensions arising from that, also in recent years the Arab revolutions in Tunisia , Libya, Egypt , Syria and Yemen all have an impact on the political and security situation in the region and the rising oil prices and their instability [27],[8].

5) Natural disasters / oil for heating

Colder weather snow and storms lead to volatility in oil prices in several European countries and the U.S. Dependence on oil for heating and increasing demand for supplies of oil as well as natural disasters may cause damage of HR and oil production facilities , leading to reduction of the amount produced and then rising oil prices [27].

***Table 3*:** Relation between oil prices and several factors

Factors	The direction with oil prices	References on this topic
Speculation	Ambiguity	[15],[82],[83],[89]
Cold weather/ Oil heating	Increase	[84],[27]
Exchange rates	Ambiguity	[85],[86],[88],[12]
War/ Revolution	Increase	[87]
OPEC policy(raise prices)	Increase	[26]
OPEC policy(raise production)	Devaluation	
Gold	Increase	[29],[103]
Non-OPEC (raise production	Devaluation	[104]
Non-OPEC (cut production	Increase	
Future contract	Ambiguity	[26]

6) OPEC policy

Organization of Petroleum Exporting (OPEC) have control and domination for the oil prices where they adjust production ratios through specific agreements, the policy of the Organization of Petroleum Exporting countries in the distribution of productivity plays an active role in the fluctuation of global oil prices [30].

7) Future contract

Future contract is an agreement between two parties will be held today to buy oil after one year with the conditions governing to ensure that the execution of the agreement [103]. The early literature stated that if the futures market is efficient, then future price is an unbiased estimator of spot price[31].Table 3 explains the relation between oil prices and several factors and Table 4 presents many factors with many models.

C. Oil price volatility and forecasting methods

The world had suffered in recent years from political instability wars and conflicts, especially in the Middle East oil-rich areas , such as the Arab Spring movements in Tunisia, Libya, Egypt, Syria and Yemen, with the acceleration of technological development . This had influences on the exchange rate in the oil market and volatile behavior of trading, in addition to the risk of supply and demand. Therefore prompting individual companies to achieve a state of profitability and stability via take different decisions is characteristically cautious and the hedging behavior. So follow-up in oil prices , monitoring the prices and the forecasting of its price movement has been critically concerned and represent an integrated part of the decision-making process for the production, export, development and transport for the owners of industries and investors. In the side of governments the issue of predicting oil prices in the short term and long term has a great significance impact on the public policy of the state and national decision-making and to build a local budget. For researchers academics perspective oil on prediction represented prominent role and deeper understanding of the issues in the economy , the financial theories , hypotheses market and Pricing of consumer goods to the citizen. According to the volatility of oil price, government policy-makers can use policy tools to adjust the stock market, reduce risk of financial market and reduce the probability of extreme risk. In addition to the need for developing models for measuring the intensity of these oscillations and predict future prices in the short term and long term. There were many attempts by researchers with different theories and models, with complex nonlinear volatility of the oil futures and irregular events and many factors the volatility of the oil futures price and an accurate forecasting on oil future prices is an important and challenging topic. From here, the aim of this study was to participate effectively in this subject and help to develop this work and investigate useful models from industries and governments.

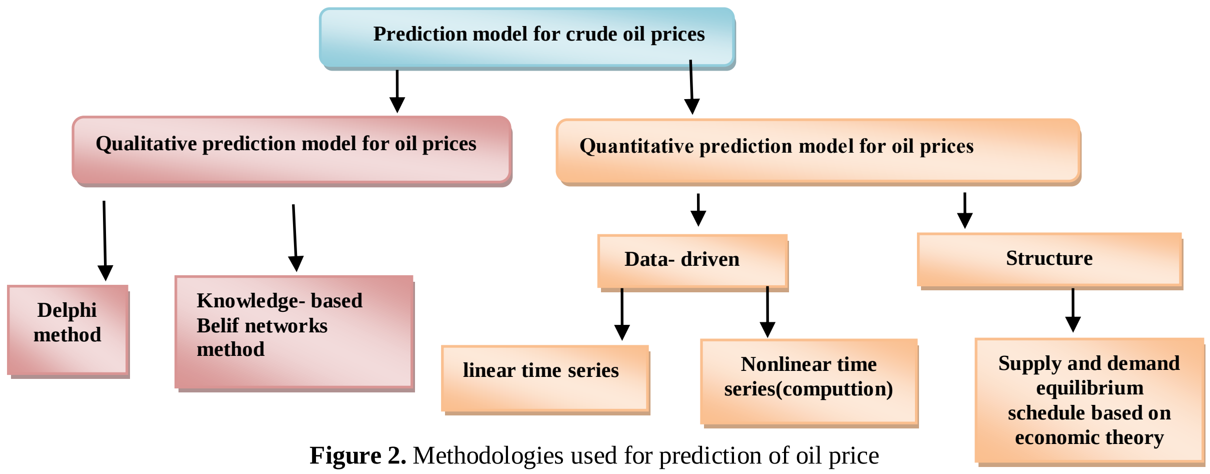

Figure 2. Methodologies used for prediction of oil price

Table 4 : Variety of factors with different models

Ref	Input factors	Models
[7]	Oil supply, crude oil distillation Capacity, oil consumption of non-OECD, USA refinery capacity, and surplus capacity.	Artificial neural network (ANN) and fuzzy regression (FR)
[32]	WTI spot price and the industrial inventories of crude Oil and petroleum products in all OECD countries	Readily available OECD industrial petroleum inventory levels
[33]	Gold	A MWRNN-based neural network ensemble learning model.
[34]	Brent	Fuzzy neural network, which combings RBF neural network, Markov chain based semiparametric model and wavelet analysis.
[6]	West Texas Intermediate (WTI)	Support vector machine (SVM).
[8]	West Texas Intermediate (WTI) and four futures contracts S&P 500, the Dollar Index, Gold, and Heating Oil..	Artificial neural networks
[35]	Years, Seasonal Demand Average price of previous week, Total number of weeks, Yearly number of weeks World events impact factor (WEIF), Global demand , NYMEX future contract prices.	Support vector machine (SVM).
[90]	Productions of OPEC countries Productions of Non-OPEC countries Proved reserves of OPEC countries Proved reserves of OECD countries Number of well drilled Demand ;Consumption of OECD countries; Consumption of China;Consumption of India Inventory;Ending stocks of OECD countries Ending stocks of US;US petroleum imports from OPEC countries US petroleum imports from Non-OPEC countries US crude oil imports from OPEC countries ;Non-OPEC countries Economy; Foreign Exchange of GBP/USD Foreign Exchange of Yen/USD; Foreign Exchange of Euro/USD US Growth Domestic Products (GDP) US Inflation rate; US Consumer Price Index (CPI) Population;population of developed countries; Population of less developed countries;WTI West Texas Intermediate price	Artificial Neural Networks

1) The qualitative methods

Qualitative forecasting techniques use theory of computation of a price with time and resource requirements and heavily relies on expert human judgment combined with a rating scale, especially when past data are not available [36]. Regarding the qualitative methods, Nelson et al. [31] presented results of the future oil prices in the California Energy Commission and used Delphi method. Abramson and Finizza [37-39] used Belief Networks (BNs) to forecast crude oil to forecast crude oil prices, However, this method shows poor level of performance and unable to face practical needs in forecasting crude oil prices.

2) The quantitative methods

In this case, no mathematical model is available and it is applied when past data are available [7]. Zhang et al. [11] divided this approach in two groups : Structure and data-driven.

(a) Structure methods: The concept of structure methods concern is to explain prediction of oil prices based on the terms of a supply-demand equilibrium schedule [11]. This approach is applied several times. For example Faris [40] investigated the world petroleum market and the determinants of crude oil price adjustment. Bacon [81] presented the factors of demand for oil and the behavior of stocks and showed forecast of crude oil. However, According to some characteristics of the crude oil market this approach has shown the difficulty [11]- [41].

(b) Data-driven methods: Besides the structural methods, a large number of data-driven methods are developed to analyze and forecast crude oil prices which were grouped in to linear models and nonlinear models .

(1) Linear time series- conventional models:

There are a number of different studies, which used time series and econometric theories in forecasting oil prices. Among them, Morana [42] investigated that Generalized Autoregressive Conditional Heteroskedastic (GARCH) models are more convenient to forecast the short term oil prices than a simple random walk model [25] . Lanza et al. [43] proved the relationships between heavy crude oil and product price using Co-integration and error correction models (EC) and evaluated the predictive power of the specification in forecasting crude oil prices [25]. Abramson et al. [44] suggested a probabilistic method for predicting oil prices. Coppola [45] proved that vector error correction (VECM) surpassed the random walk model (RWM). Hog and Tsiaras [46] applied Auto regressive Conditional Heteroskedasticity Models (ARCH) to study the benefits of utilizing the forward-looking information that is included in the prices of derivative contracts. Cabedo and Moya [47] developed the Historical Simulation with Auto-Regressive Moving Average models (ARMA) to estimate oil price VaR Forecasts. However, the traditional econometric models consider that the oil price series is linear or near linear. In fact, crude oil price was described as a complex and chaotic phenomenon.

(2) Nonlinear Time Series Modeling

Non linear models include computation model such as:

Artificial neural network model

Motivated by biological method its main purpose was to investigate the human brain. artificial neural network ANN can learn and take a broad view from Knowledge ANN has been used for a great range of responsibilities in many different fields such as commerce, industrial and science [48]. Amongst ANNs, the back propagation (BP) has increasingly become a unique neural system model and has been used most widely. The BP process, set up by Rumelhart et al. [49] was a supervised learning technique for teaching multilayer supply forward neural networks. Numerous experiments have applied the use neural network such as Haidar et al. [22] used feed forward back propagation NN composed of three layers by using two groups of inputs and crude oil benchmark markets namely (WTI) and European Brent crude oil (Brent). The proposed forecasting tool evaluated by multi metrics such as hit rate coefficient which appears to support that heating oil spot price has significant explanatory power for predicte crude oil spot price[25]. Yu et al. [50] implemented the EMD-based neural network ensemble learning model for forecasting crude oil spot price ,then compared proposed model with different metods their results concluded that the new model is promising for oil price prediction . Alizadeh and Mafinezhad [51] applied a General Regression Neural Network (GRNN) model to predict Brent oil price in the short term. By containing seven kinds of attributes as inputs, the authors claimed that their constructed model has provide a good results under critical conditions [25]. Ma [52] developed symbiotic evolutionary immune clustering algorithm to determine automatically the hidden layer number of RBF network and from combination of this model predicts oil prices. Other exist studies in the literature which applied ANNs for oil price forecasting or to investigate the relationship between oil and other economics such as Panella et al. [53]; Malik et al. [54]; Lackes et al. [78]; Malliaris and Malliaris [80]. The neural network model can be trained to approximate any measurable nonlinear function However, it suffers from local minima, over-fitting, poor generalization performance and the difficulty of determining appropriate network architectures.

Wavelet decomposition

Wavelet decomposition clearly emerged in the literature exhibiting them. Jammazi and Aloui [21] employed a flexible model to forecast crude oil price based on the dynamic characteristics of MBPNN and Haar A Trous wavelet (HTW) decomposition. Their experiment covered the period from January 1988 to March 2010.Yousefi et al [55] investigated the efficiency of the economic market in price future markets for NYMEX oil futures based on wavelets. Among these studies wavelet integrated with other methods to get the best results Alexandridis et al. [56] devoted monthly West Texas Intermediate (WTI) crude oil spot prices to develop new predictive models by combining wavelet with neural networks then compared their results econometric forecasting approach. Mingming et al [33] employed multiple wavelet recurrent neural network (MWRNN) using crude oil and gold prices model the experimental results achieved high accuracy for prediction. He et al. [57] implemented wavelet analysis and artificial neural network model in three main markets and the results shows that proposed model outperform the classic approaches. Wavelet decomposition seems to be an efficient and powerful tool for crude oil price forecasting. However, the main drawback of this method is the loss of information due to biases are displayed at every step of the filtering when violation occurred for model defaults.

Support vector machine

Support vector machines (SVM) are supervised learning models used for classification and regression analysis. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible [25]. Xie et al. [6] Suggested a new model for predicting oil price based on support vector machine (SVM) they used West Texas Intermediate (WTI) crude oil from January 1970 to December 2003 then they compared the performance of the proposed model with ARIMA and BPNN the results showed superiority SVM on the other two methods. Jun et al. [58] utilized a hierarchical support vector machine model (SVM) for oil price predicting. According to results the proposed model is outperformed than two methods SVR model and BP neural network. Khashman et al. [35] used support vector machine (SVM) for weekly of West Texas Intermediate (WTI) crude oil cover period from 03 January 1986 to 25 Dec 2009 for predicting oil price. The authors obtained experimental results that a reasonable degree of accuracy. Zhu et al. [59] explored the historical data from NYMEX market under the clustering method and support vector machine (SVM) models .Performance is measured using a statistical standard mean squared error (MSE), mean absolute error (MAE), mean absolute percent error (MAPE) and directional consistency statistics (DCS). Results indicated to improve forecasting accuracy. However , the prediction accuracy of the single forecasting model needs to be improved and long time consuming when a large size of data, so we need to integrate SVM with approximate algorithms to reduce the time [105].

Hybrid models

Hybrid methods have emerged in the recent years, the basic idea of which is to complement the disadvantages of the individual models and generate synergy effect on the results to predict oil prices. Guo [23] developed a new model combining between genetic algorithm (GA) and Support Vector Machine to forecasting Oil Price. To validate the model they used Brent oil stock price data from 2001/12/27 to 2011/10/30. Experimental Results proved that new model GA-SVM is better than performance of traditional SVM. Azadeh et al. [7] developed a new model based on artificial neural network (ANN) and fuzzy regression (FR) to predicting oil price through different inputs such as the oil supply, crude oil distillation capacity ,oil consumption of non-OECD, USA refinery capacity, and surplus capacity their results indicated that proposed model be adjusted and applied easily. Liu et al. [34] suggested a new approach to predicting oil price based on a fuzzy neural network, which include RBF neural network, Markov chain based semiparametric model and wavelet analysis. Authors used Brent oil price series for the period 20 May 1987 to 30 August 2006. Several studies were attempted to predict oil prices merging between two or more techniques and is detailed below.

Ensemble methods

Ensemble techniques are learning algorithms that create a set of multiple classifiers and then categorize new numbers of data by taking an average or vote of their prediction results [95]. It has caught the attention of scientist from a number of areas, for example Neural Networks , Pattern Recognition, Statistics and Machine Learning etc. [97]. The stimulus of combining many classifiers is to improve the outcome and performance. Several previous works illustrated that the ensemble constructed significant performance and more accurate results than the individual methods [96 - 101]. Baker et al. [94] proved that artificial neural network pedotransfer functions (ANN–PTF) ensembles surpassed individual ANNs, under the same condition to predict. Partalas et al. [97] presented a general theoretical framework for the greedy ensemble by selecting relatives of regression ensembles models to monitor water quality. Li et al. [102] proved that three different selective ensemble format contains an ensemble forward sequential selection, hill-climbing, ensemble backward sequential selection have parallel generalization performance.

III. Bench Datasets Used, Data Conditioning and Performance Evaluation

Literature presented predicting oil prices with different classifications of data including timetables for data: Daily, weekly, monthly or yearly. For example, short-term refers to predicting within 1 - 5 days of the future [8] and to implement measures to reduce the risks in the long term for forecasting the coming years [93]. Some prefer to deal with weekly or monthly data because daily data are incomplete as a result of the weekend or shut down the market as an outcome of sudden events [6]. Table 6 illustrates some examples of data used in the past.

A. Crude oil prices benchmarks

Crude oil price benchmark is the standard or the pricing of raw materials. It is a combination of materials that are traded freely in the money markets and the future in accordance with the terms and conditions of specific laws. There are many major benchmarks in the international oil market, but according to previous studies, we used three benchmarks namely West Texas Intermediate in North America (USA), Brent (North Sea) in Europe and Africa and Dubai/Oman (Middle East)[69], which plays an important role as a reference point to determine the price of other related crude oils available. Table 6 shows the data frequency and crude oil price benchmarks used in previous articles.

B. Pre-Processing

Before applying the proposed models, we have a necessary step which is called data processing. Data is collected and often these data contains a percentage of the noise so it is converted to the appropriate format to filter data and enhance the prediction using several methods, including normalization and may also need to divide the data, for example, training and testing data [6].

Table 6 : Types of data set and benchmarks

Ref	Year	Period	Prediction Horizon	Crude oil prices benchmarks
[5]	2012	2 January 2002 to 26 August 2011	Daily	WTI & Brent
[8]	2009	Jan 1996 to Aug 2007	Daily	WTI
[10]	2010	Model A: from January 1986 to July 2007 Model B :January 1992 to August 2006	Monthly	WTI
[9]	2011	January 1988 to December 2009	Monthly	Brent
[65]	2009	January 2005 to May 2008	Weekly	----
[4]	2009	Jun 2008 to Feb 2009	Monthly	WTI
[23]	2012	27/12/2001 to 30/10/2011	Daily	Brent
[70]	2010	2January1991 to 9 October 2001	Daily	WTI
[7]	2012	1985 to 2007	Annual	-----
[32]	2005	January 1992 to April 2003	Monthly	WTI
[6]	2006	January 1970 to December 2003	Monthly	WTI
[50]	2008	1 January 1986 to 30 September 2006 20 May 1987 to 30 September 2006	Daily Daily	WTI Brent
[71]	2008	1January 2000 to March 31, 2008	Daily	WTI & Brent
[34]	2007	20 May 1987to 30 August 2006	Daily	Brent
[59]	2008	March 2003 to February 2006	Daily	WTI
[72]	2009	January 6, 1992 to December 29,2006	Daily	Brent, Dubai and WTI
[92]	2002	From 1981 to 2002	Daily	Brent, Dubai and WTI

Also one of the data processing methods is to remove non-contributing factors (features or variables) that do not contribute to the prediction or improve the performance. Having a large number of these factors lead to the complexity of the model and reduces the accuracy of the prediction, as well as when it is few number of variables, the results can be interpreted easily [32]. Gabralla et al. [25] used daily data from 1999 to 2012 to predict the West Taxes Intermediate and three different algorithms the Best - first, genetic algorithm based search methods for feature (attribute) selection . Table 7 illustrates more pre-processing methods.

C. Performance Evaluation

According to the literature, assessing and measuring the performance of prediction models are done by calculating certain criteria, such as: Mean Relative Square Error (MRSE), Mean Relative Absolute Error (MRAE), Mean Relative Square Deviation (MRSD), Mean Relative Absolute Deviation(MRAD), Root Mean Square Error (RMSE), R-square (R2), Mean Square Error (MSE), Mean Absolute Error (MAE), Sum of Squared Errors (SSE) , Directional accuracy (DA), Maximum absolute error (Max AE) and Direction Statistics (Dstat) [6] [50]. Table 7 shows examples for pre-processing and performance measures.

IV. Conclusions

Considering the problems of predicting oil prices most of the research and studies are complicated as a result of the volatility and changes in irregular oil prices, with the presence of many of the factors that affect these fluctuations. This article attempted to review numerous essential issues and current developments of prediction of oil prices. These include the link between economic variables and volatility of the oil prices and the role of the primary factors in fixing prices of the oil. Several methods have been investigated and works reposted in the literature illustrate that the prediction were accurate even though many different data sets and tools were used to measure performance of the proposed models. However, there still remain unsolved or partly solved issues. More research should be dedicated to developing more effective and efficient methods in feature selection and prediction of oil price to assess more successful outcomes in the future.

Table 7 **:** Pre-processing steps and performance metrics

Ref	Pre-processing	Performance evaluation
[60]	Segmentation of the dataset to testing and training . Partial Autocorrelation furct (PACF) to find the maximum number of lags. Construct a sliding window of size L+1	Mean absolute error (MAE) Mean absolute percentage error(MAPE) Sum of square error (MSE) Root mean square error (RMSE) R-square (R2) Ratio of model RMSE to random walk RMSE(U2-Theil) Directional accuracy (DA) Maximum absolute error (Max AE)
[32]	Normalized total OECD industrial petroleum inventory Three lags plus the current period of relative inventories,	Root mean square (RMSE), Mean absolute deviation (MAE), Mean absolute percent error (MAPE) statistics, Theil inequality coefficient, Bias, variance and covariance proportions
[33]	Partition 60% data were used to train, 10% to validate, and 30% to test	Mean relative square error (MRSE) Mean relative absolute error (MRAE) Mean relative square deviation (MRSD) Mean relative absolute deviation (MRAD)
[34]	Wavelet decomposition approximation	Coefficients of resolution approximation RMSE check out criterion
[6]	Data normalization Data divided into in-sample data and out-of-sample data.	Compare its performance with those of ARIMA and BPNN based on root mean square error (RMSE) and direction statistics (Dstat)
[8]	The data set was divided into the training and test sets, 90% of the data for training and 10% for out-of-sample tests Data normalized	Root Mean Square Errors (RMES) R-square (R2) Mean Square Error (MSE) Mean AbsoluteError (MAE) Sum of Squared Errors (SSE)
[35]	Input features are scaled to values between 0 and 1.For training and testing are coded to suitable output classes.	Calculate correct prediction rate

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